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A Hybrid Model for Sales Forecasting in Healthcare Supply Chain

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Abstract

In this paper, a hybrid model is developed for drug time series in the healthcare supply chain. The model helps to make decisions about the strategic issues such as optimizing inventory and integrating healthcare supply chain. In order to verify and analyze the proposed model, the data was obtained from a real company. The model has practical significance after experiencing and managerial insights are provided.

Key words: Drug time series; Healthcare supply chain; Forecasting

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INTRODUCTION

Supply chain is now becoming increasingly important in competitions between rivals. The supply chain is the connected series of interdependent firms involved in the flow of goods, services to the customer. There are a considerable number of studies devoted to improve the efficiency of supply chain. Despite the various perspectives, it is widely acknowledged that the final customer's demand sets the entire supply chain in motion (Syntetos et al., 2016). Due to the critical role of the demand, it is significant to identify supply or demand fluctuations to decrease resource utilization and improve the integration. So forecasting is an important part of SC strategies.

The healthcare supply chain is different from other Manufacturing supply chains for its complex operations and organizations. It is difficult to control or predict the production schedules. While numerous studies payed attention to price profile, cost reduction and system integration. Some studies formulated a mixed-integer linear programming model to select both a product development and introduction strategy and a capacity planning and investment strategy (Papageorgiou et al., 2001). Some paper studies the technical flow and highlights its particular requirements (Marcelo & Nakano, 2009). Some informed that new drug pricing mechanism is the key to the current healthcare reform and should be implemented in coordination with other health system reforms (Yu et al., 2010). Jagjit Singh Srai (2015) studied on three cases to demonstrate the utility of the approach in assessing the supply network and system integration opportunities that emerge from the continuous processing of healthcare products. There is little research worked on forecast the demand in healthcare supply chain.

It is said that the Big Data era has come. Big data, in many ways, is a poor term. All industries have its large volumes of data collected at unprecedented speeds, which are a treasure if used reasonably. Besides its huge volume, the complex structure and rational use really get people thinking. In supply chain, there are several of data from interior and exterior such as consumption and the amount of supplies.

1. LITERATURE REVIEW

There are massive of studies contribute to the prediction on products like energy, but little researches on healthcare. It is not always accurate to have complicated forecasting techniques, some simpler approach can be more effective in some situations (Makridakis & Hibon, 2000). Stonebraker and Keefer (2009) formulated a latent therapeutic demand (LTD) model which captures how physicians would prescribe treatment and how patients would comply if ample supplies of drugs were available and affordable to forecast potential demand for supply-constrained as well as brand-new drugs. Konstantinos et al. (2016) put eleven methods including diffusion models (Bass model & RPDM), ARIMA, exponential smoothing (Simple and Holt), naïve and regression methods, ARIMA and Holt produce accurate short term (annual) forecasts into forecasting the branded and generic drugs.

1.1 Time Series Forecasting Method

Forecasting in marketing depended on historical daily, weekly or yearly sales data. Traditional methods include the Auto-regression (AR), Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA) and smoothing methods is popular to be used in time series analysis. While traditional time series forecasting method sometimes always work but its degree of accuracy should be improved. The linear model is not always effective in the real world. When the data is nonlinear, it is not suitable to use ARIMA models solely.

In order to overcome the limitations, Machine Learning method has been brought in to optimize the models. Machine Learning is evolved from the study of pattern recognition and computational learning theory in artificial intelligence. It based on that a signal will feedback to a system to be categorized into three type: Supervised learning, unsupervised learning and Reinforcement learning. Neural networks, decision trees are common method in forecasting. Ansuj et al. (1996) proposed a hybrid method of ARIMA and back propagation neural networks to predict sales. Zhang (2003) combined both ARIMA and ANNs to take advantage of the strengths from two models. Chen et al. (2016) proposes a novel grey wave forecasting method with contour time series to predict metal price. The examples are more in energy industries. Although the characteristic of data in different industries is not same, while the forecast methods afford us lessons. Yu et al. (2008) proposed an empirical mode decomposition (EMD) based on neural network ensemble-learning for the forecasting of the world oil price. Tao et al. (2013) added strategy such as iterated strategy and MIMO strategy into the oil price prediction algorithm. Humphrey et al. (2016) formed a Bayesian artificial neural network (ANN) statistical forecasting model to support water resource decision making.

1.2 Healthcare Forecasting Method

Models of sales forecasting in healthcare supply chain is few. Among all the studies on healthcare supply chain, only a small proportion of these studies directly with sales forecasting about healthcare products. Konstantinos et al. (2016) use eleven methods including diffusion models (Bass model & RPDM), ARIMA, exponential smoothing (Simple and Holt), naïve and regression methods to forecast drug time series. Some studies formed new hybrid time series model. Mousazadeh et al. (2015) developed a bi-objective mixed integer linear programming (BOMILP) model for the healthcare supply chain network design problem.

2. THE HEALTHCARE SUPPLY CHAIN

Forecast the demand in the healthcare supply chain is not the same as others. A typical healthcare supply chain consists of primary manufacturing, secondary manufacturing, market warehouses/distributions, wholesalers and retailers/hospitals (Shah, 2004). The healthcare industries provide verities of products like drugs, medical apparatus, health aids. The pharmaceutical products in healthcare industries are critical in ensuring a high standard of care for patients. The role of healthcare products highlighting the need for efficient management of the healthcare supply chain. The healthcare industry, which could be considered as an immense global industry, can be defined as a complex of processes, operations and organizations involved in the discovery, development and manufacturing of medications and drugs (Ibid.).

3. METHODOLOGY

In this paper, we aimed to research the sale of a healthcare product labeled A in a famous healthcare company. The product is one of the endoscopic cutter which is used in gastrointestinal surgery. An endoscopic cutter is an instrument that helps the doctor to view and operate on the internal organs and vessels of your body. That means it allows the doctor through a small cut in your organ without making large incisions. The dimension of the cutter makes the different type of products. There is another product labeled B is a completion of the A product. On another hand, there is a set of data means the amount of hospital obtained from SFDA. First, we forecast the trend of product A based on the time series theory. Then, we put the influencing factors to perfect the whole model. We use R language to run the model.

3.1 Data

Our model uses daily sales data as input for an ARIMA. The data were obtained from two year sales of the healthcare company. The sale of product B is obtained from the competitor. In forecasting the sale of a healthcare product, there are lots of possible influencing factors such as price, sales channels, policy and so on. But in this research, we concern ourselves with historical data of product A, product B and the amount of hospital, because these two factors significantly affecting the product A.

3.2 Autoregressive Integrated Moving Average (ARIMA)

ARIMA have dominated lots of areas of time series forecasting. The popularity of this model is due to its statistical properties in the model buildings. The ARIMA model has no seasonal parameters. There are three parameters in this model which build up ARIMA (p,d,q). p and q are all integers, where, p is the number of autoregressive terms and q means the number of lagged forecast errors of the equation. d is also an integer which means the order of differencing. That is, the model has the following form:

Where y_t and a_t are the actual value and random error at time period t, respectively $\emptyset(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i$, $\theta(\mathrm{B}) = 1 - \sum_{j=1}^{q} \theta_j B^j$ are polynomials in B of degree p and q, (i=1,2,…,p) and θ_i(i=1,2,…,q) are model parameters. The methodology includes three iterative steps of model identification, parameter estimation, and diagnostic checking. The basic idea is that if a time series is generated from ARIMA process, it should have some theoretical autocorrelation properties. It is possible to identify one or several potential models by calculating the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

Ensuring the time series stationary is required in data transformation stage. Therefore, data series has statistical characteristics such as a mean and variance that are constant over time. When the time series present trends, it is necessary to stabilize the trend by differencing the data. Then, the time series are estimated by minimizing the measure of errors. The result can be achieved on using an optimization procedure. If the model is not adequate, a new model should be built up by matching the ACF and PACF, which are followed by the procedures above. Also, several criteria can be used to examine the fit of the model, such as the Akaike's information criterion (AIC) (Shibata, 1976) the Bayesian information criterion (BIC) (Schwarz, 1978). The satisfactory model can be selected by repeating the three steps.

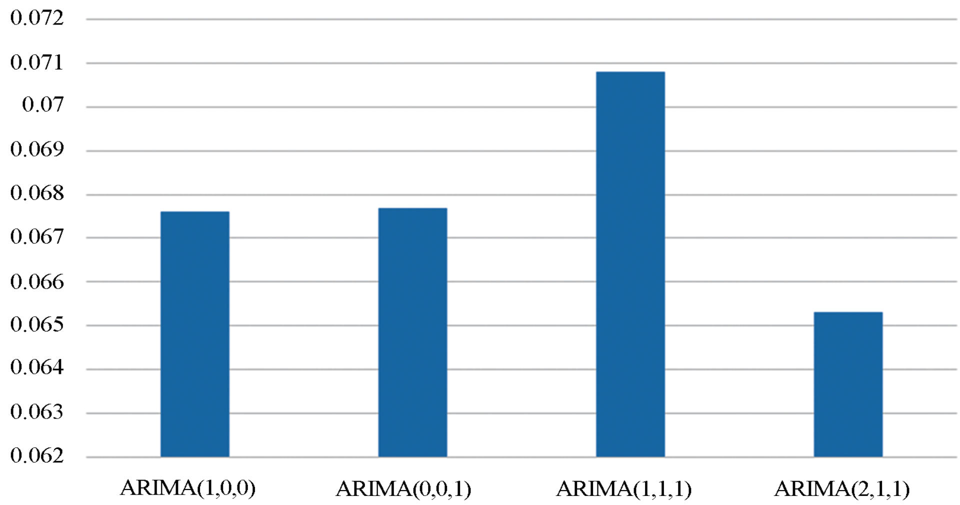

Figure 1
Average of RMSE Result Based on Normalized Values

3.3 Boosting Algorithm

Boosting is a learning algorithm that can make up a highly accurate hypothesis by combining many weak algorithm. Each weak algorithm can be used to generate a predicted classification for any instance. After weighting the outcomes of weak algorithm, the final result will be more accurate. In this paper, we aimed the AdaBoost algorithm. Similarly, AdaBoost is a classifier which focus the learning attention on different examples of this set using adaptive weights ($\omega_b(i)$), in contrast to other ensembles as Bagging which do not update the weights. After finishing the training process, the single classifiers obtained are combined into a final and more accurate classifier.

The theory most widely used is given by Freund and Schapire. The algorithm has the following form:

i. Start with $\omega_b(i) = \dfrac{1}{n}, i = 1,2, \dots, n$.

ii. Repeat for b=1, 2, … , B.

a) Fit the classifier $C_b(x) \epsilon \{-1,1\}$ using weights $\omega_b(i)$ on T^b.

b) Compute: $\varepsilon_b = \sum_{i=1}^{n} \omega_b(i) \xi_b(i)$ and α_b=ln((1-ε_b)/ε_b).

c) Update the weights $\omega_{b+1}(i) = \omega_b(i) \cdot \exp\,(\alpha_b \xi_b(i))$ and normalize them.

iii. Output the final classifier $C(x)$=sign(($\sum_{b=1}^{B} \alpha_b C_b(x)$)).

A training set is given by T_n={(x_1,y_1), (x_2,y_2),..,(x_n,y_n)} where takes values of {−1, 1}. The weight $\omega_b(i)$ is assigned to each observation Xi and is initially set to 1/ n. This value will be updated after each step. A basic classifier denoted $C_b(x_i)$ is built on this new training set,T_b, and is applied to each training sample. The error of this classifier is represented by ε_b and is calculated as $\varepsilon_b = \sum_{i=1}^{n} \omega_b(i)\xi_b(i)$ where

$$\xi_b(i) = \begin{cases} 0 & C_b(x_i) = y_i \\ 1 & C_b(x_i) \neq y_i \end{cases}.$$

The new weight for the (b+1)-th iteration will be $\omega_{b+1}(i) = \omega_b(i) \cdot \exp(\alpha_b \xi_b(i))$, where α_b is a constant calculated from the error of the classifier in the b-th iteration. More specifically, according to the authors mentioned above $\alpha_b=\ln((1-\varepsilon_b)/\varepsilon_b)$.

The calculated weights are then normalized so that they add up to one. Accordingly, $\varepsilon_b=0.5-y_b$, where y_b shows the advantage of the basic classifier of the b-th step over the default rule in the worst case, where both classes have the same a priori probability (0.5). Therefore, the weights of the wrongly classified observations are increased and the weights of the correctly classified ones are decreased, forcing the single classifier built in the following iteration to focus on the hardest examples. Furthermore, the differences when the weights are updated are greater when the error of the single classifier is small since more importance is given to the few mistakes mentioned when the classifier achieves a high level of accuracy. The alpha constant can therefore be interpreted as a learning rate which is calculated as a function of the error made on each epoch. This constant is also used in the final decision rule giving more importance to the individual classifiers that made a smaller error.

This process is repeated in every step for b=1, 2, 3,…, B. Finally, the ensemble classifier is built as a linear combination of the single classifiers weighted by the corresponding constant α_b.

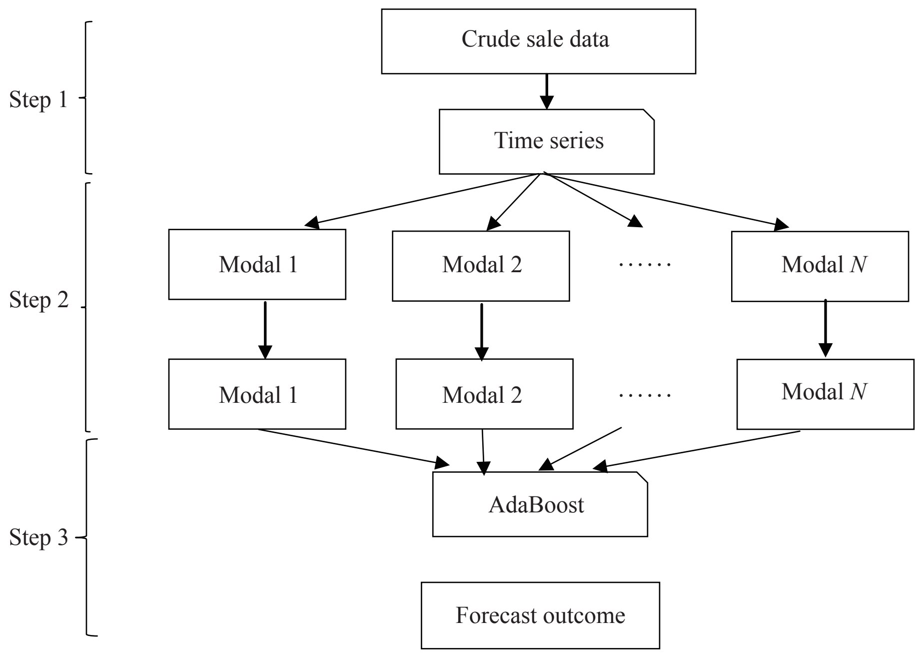

Figure 2
The Proposed Hybrid Model Framework for Sales Forecasting

3.4 Evaluation Metrics

To compare the different model, we use the symmetric mean absolute percentage error (SMAPE) and mean absolute scaled error (MASE). SMAPE is a main measure for many forecasting competition, while MASE (Hyndman & Koehler, 2006) has more feathers better than SMAPE. The definition of these two criterial as follows:

$$\text{SMAPE}=\frac{1}{M}\sum_{t=1}^{M}\left|\frac{F_t-A_t}{F_t+A_t}\right| \times 100 ,$$

$$\text{MASE}=\frac{1}{M}\sum_{t=1}^{M}\left|\frac{F_t-A_t}{\frac{1}{N-1}\sum_{i=2}^{N}|F_t-F_{t-1}|}\right|.$$

Where is the forecast, is the true time series value, M is the number of observations in the holdout sample, and N is the number of observations in the estimation sample. After prediction modeling, the data are rescaled back following the reverse of the data normalization, and all accuracy measures are calculated based on the original scale of the data.

CONCLUSION

In this paper, a hybrid model is proposed for sales forecasting in healthcare supply chain. Researches in healthcare supply chain is few. The model considers not only historical data but many influencing factors.

Our experimental results show that our proposed model is fit for sales forecasting. While there still are lots of factors may influence the sales such as policy, especially in China. In our future research, we will study the policy acting on the sale to enhance the sales forecasting.

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